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Uses of AI in Field of Radiology- What is State of Doctor & Patients Communication in Different Disease for Diagnosis Purpose

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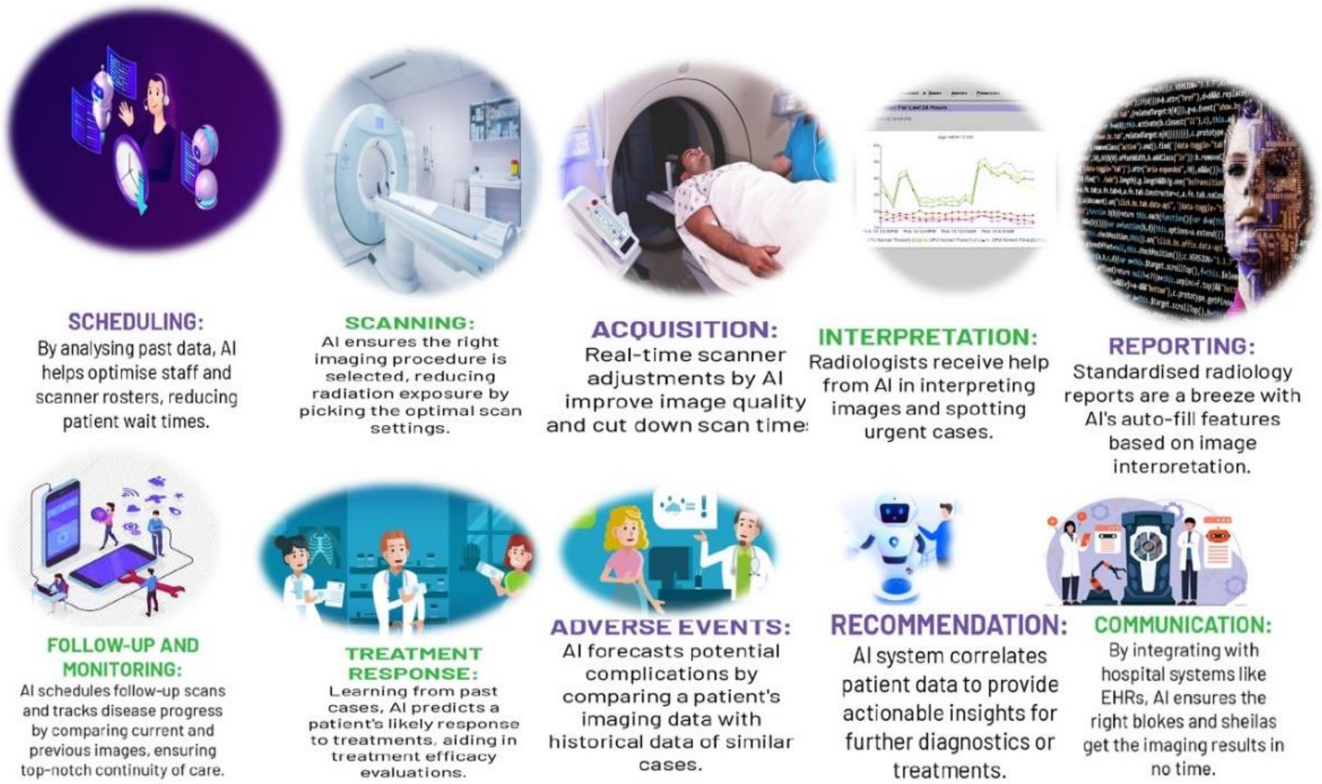
GRAPHICAL ABSTRACT



ABSTRACT

Over the course of the past ten years, there has been a rising interest in the application of AI in radiology with the goal of improving diagnostic practises. Every stage of the imaging workflow might potentially be improved by AI, beginning with the

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ordering of diagnostic procedures and ending with the distribution of data. One of the disadvantages of utilising AI in radiology is that it can disrupt the doctor-patient contact that takes place during the diagnostic procedure. This research synthesis examines how patients and clinicians engage with AI in the process of diagnosing cancer, brain disorders, gastrointestinal tract, and bone-related diseases. [S]ome of the diseases that are studied include cancer, brain disorders, and gastrointestinal tract. Researchers began their investigation of several databases in 2021 and continued their work until 2023. Some of the databases that were examined include PubMed, Embase, Medline, Scopus, and PsycNet. The search terms "artificial intelligence" and "intelligence machine" as well as "communication," "radiology," and "oncology diagnosis" were utilised. It has been demonstrated that artificial intelligence can help medical professionals make more accurate diagnoses. Medical compliance can be enhanced with good training in doctor-patient diagnosis communication, and future research may assist boost patients' trust by informing them of the benefits of AI. Both of these things are important for the delivery of quality medical care.

Keywords- AI, Radiology, Doctors-patients Communication, Disease diagnosis.

I. INTRODUCTION

The fields of science and medicine are not immune to the revolutionary effects of artificial intelligence (AI) and machine learning (ML). Machine learning (ML) is a subset of artificial intelligence (AI) in which computers or tools learn from data to generate classifications or predictions with or without human supervision1[1]. AI refers to the development of robots or programmes that can replicate human thought and conduct. The development of high performance computers has hastened progress in several areas in recent years[2].

Digitised areas of medicine, such as imaging, are ideally suited to be the first to implement AI and ML. To efficiently capture such data for AI and ML, the entire imaging process is conducted in the digital environment, from the acquisition of images to their reconstruction, analysis, reporting, and communication[3]. It seems especially likely that radiologists will be the first to explore and implement new technologies as primary users for cancer imaging, given this is a sizable amount of the workload for many departments[4]. In particular, this is the case because such tasks can be monotonous (for example, in cancer screening, where readers must sift through a large volume of normal studies to identify abnormalities), time-consuming (for example, when taking serial measurements of tumours), and taxing (when outlining tumours for disease segmentation)[5]. In fact, several commercial devices are now available in the cancer imaging market with the goals of increasing productivity, decreasing error rates, and bettering diagnostic accuracy. However, many technology solutions are being developed in silos, making it difficult for them to gain widespread clinical adoption. The development, testing, validation, and adoption of such tools may have been hampered by the lack of opportunities for clinicians, radiologists, scientists, and other experts to interact collectively to understand the clinical and data science landscape[6]. To do this, it is necessary to foster ecosystems that span multiple disciplines and sectors, with the help of commercial partners when applicable. The purpose of this review is to encourage dialogue amongst different fields on these topics[7]. We provide an overview of applicable AI and ML methods and identify important openings for their use in cancer imaging. We explore the clinical, professional, and technical hurdles that stand in the way of integrating AI and ML into cancer imaging[8]. We extrapolate from past experience and look ahead to the technical and infrastructural advancements that will be required to enable AI in cancer imaging, paving the way for the seamless incorporation of AI and ML technologies into healthcare infrastructure and the preparation of a well-trained, future workforce[9].

II. MATERIAL & METHODS

A literature analysis was conducted to determine whether or not artificial intelligence (AI) was used by radiologists in communicating cancer diagnoses to patients. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria were used to conduct and report the systematic review (Figure 1)[10]. There has been no registration of this systematic review's procedure. From 2020 to 2023, we searched PubMed, EMBASE, Medline, Scopus, Psycnet, and Medline In-process, among other digital literature databases. Because of the rapid pace of change in IA in radiology and the significance of psychological factors like doctor-patient contact, only research published in the recent decade were included in the analysis[11]. MeSH was utilised to find label terms in order to get as many relevant articles as feasible. The terms "artificial intelligence" or "intelligence machine" and "communication" and "radiology" and "oncology diagnosis" were utilised across all disciplines as keywords and descriptors[12].

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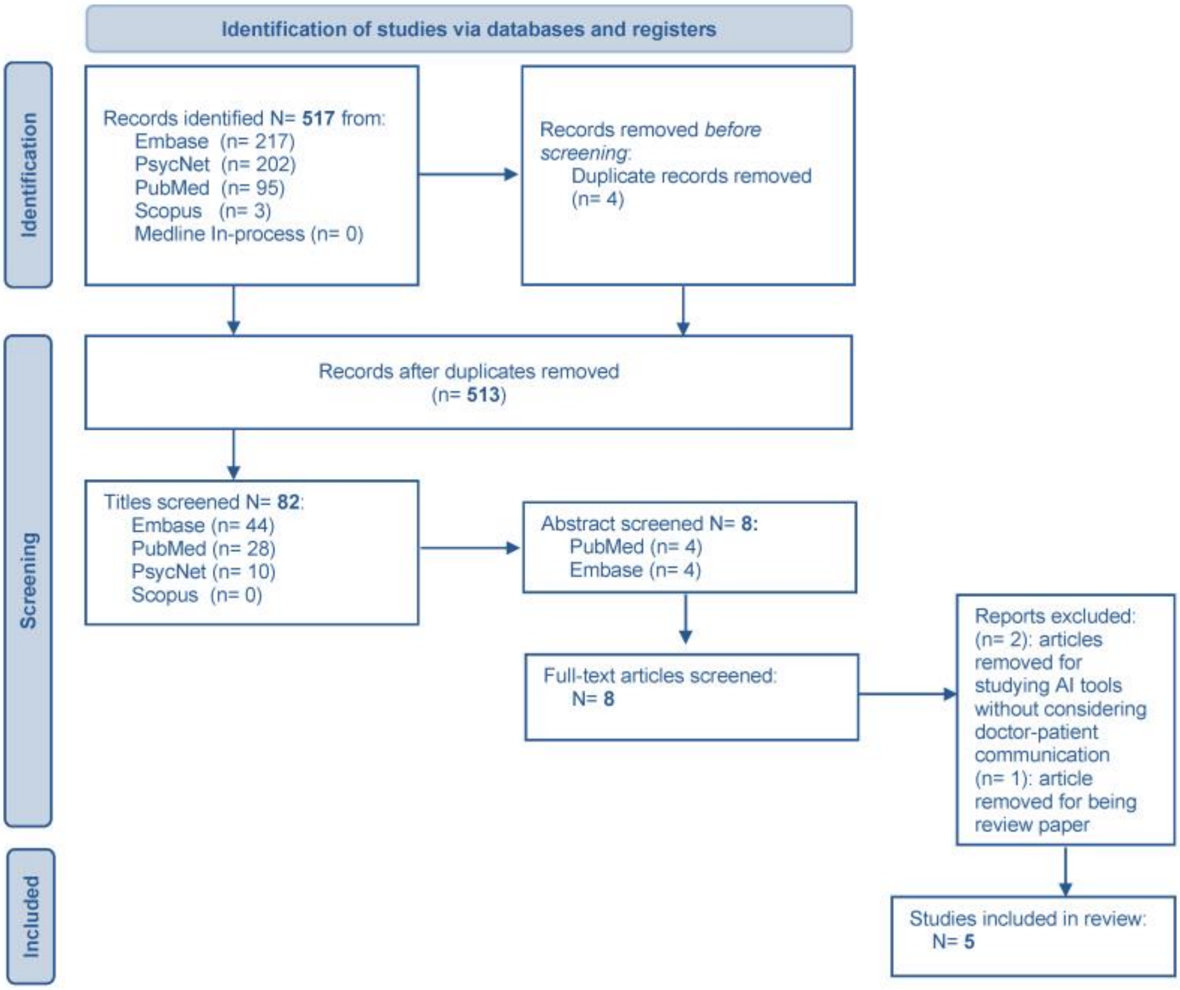

Figure 1 is a flowchart depicting the procedure for selecting studies to include in a Preferred Reporting Item for Systematic Review (PRISMA).

III. INCLUSION AND EXCLUSION CRITERIA

No restrictions were placed on language or age range, and all publication formats and study designs were welcome. Studies that reported the advancement of AI in radiology for cancer diagnosis were considered, as were those focusing on the communication of oncological diagnoses, those exploring the perspectives of patients regarding these diagnoses from the perspective of their doctors, and those examining the role of AI in screening mammography. Research publications that dealt with the application of AI in areas other than medicine were also disregarded[13].

IV. SCREENING AND DATA EXTRACTION

The literature search for inclusion and exclusion criteria resulted in two reviewers (A.D. and S. F. M. P.) assessing all titles and abstracts. All of the members of the study team had a discussion to settle the differences[14].

V. RESULTS

There were a total of 517 publications found, and 4 duplicates were weeded out before the first round of screening. Next, we screened the titles and abstracts to eliminate 125 articles and 28, respectively. Eligibility was determined for eight full-text articles. Two articles were removed because they focused on AI tools without taking doctor-patient contact into account, and one article was removed because it was a review. Five studies were included after the whole text was screened[15].

Ahmad John (2021): There were a total of 517 publications found, and 4 duplicates were weeded out before the first round of screening. Next, we screened the titles and abstracts to eliminate 125 articles and 28, respectively. Eligibility was determined for eight full-text articles[16]. Two articles were removed because they focused on AI tools without taking doctor-patient contact into account, and one article was removed because it was a review. Five studies were included after the whole text was screened[17].

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By supplying qualified radiologists with pre-screened images and identified features, an AI component incorporated into the imaging workflow would boost productivity, reduce errors, and fulfil objectives with minimal manual input. As a result, many people and organisations are working to develop artificial intelligence in medical imaging. Radiologists rely heavily on the ability to quantify and evaluate radiographic properties from images to complete their work[18]. These features may be relevant for the clinical task at hand, such as disease diagnosis, characterisation, or monitoring. Since the early 1960s it has been suggested that logic and statistical pattern recognition be applied to medical problems. With the advent of personal computers in the 1980s, a number of clinical procedures have been automated using artificial intelligence, transforming radiography from a perceptually subjective trade into a quantitatively computable domain. The tremendous rise of data and computational power is directly correlated to the accelerating pace at which AI is transforming radiology[19].

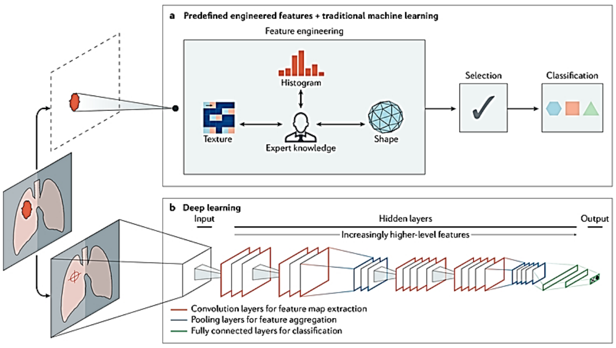

Figure 2: Applications of AI in diagnostic imaging.

For a typical classification task, such determining whether an object is benign or malignant, this diagram illustrates two AI approaches. The first technique uses expert-guided feature engineering to glean information from targeted areas[20]. Tumour volume, shape, texture, intensity, and location are all examples of these characteristics used to characterise cancer. Machine learning classifiers are fed just the most reliable features. b | The second approach relies on deep learning and can get by with just localization instead of region annotation. During training, the system's several layers work together to extract features, narrow down the options, and make a final classification. Earlier layers may learn simple forms like lines and shadows, whereas deeper layers may learn complex structures like organs or complete things (Box 1). Radiomics, which is based on data and radiology, encompasses both approaches[21].

European society of radiology (2021): Radiologists learn their craft over the course of several decades, during which time they are exposed to thousands of tests and instructed to interpret them using a combination of reading skills and clinical knowledge. The number of exams interpreted and the precision of visual image analysis are two of the most important factors in becoming a skilled interpreter. Using deep learning technologies, AI can do image interpretation and extract not just visual but also quantitative information, such as Radiomic signatures or other imaging biomarkers that the human brain would not recognize[22]. The use of AI to view and analyse images is on the horizon. It has been suggested that trainees may not develop sufficient interpretation abilities if they do not perform enough direct ("unaided") interpretations during their training years if software is used in the interpretation process. Trainees will benefit from AI's assistance in making more accurate interpretations, but there is a risk that future radiologists would become overly reliant on such software[23]. There has to be a dedicated AI and informatics section in future radiology training programmes so that students may learn how to effectively incorporate AI into radiology practise. The introduction of AI into our working lives is inevitable. To ensure that patients' best interests are constantly protected, we must collaborate with programmers and computer engineers to facilitate the integration of AI tools into our workflows (PACS/RIS systems, task automation, etc.)[24]. There are two major categories of AI techniques currently in widespread usage. The first employs mathematically defined, hand-engineered properties (such tumour texture) that may be quantified using software31. Modern machine learning models are fed these features during training so they can better categorise patients and aid in clinical decision making. While such features may be thought of as discriminative, they are dependent on expert definition and may not be the best feature quantification strategy when trying to accomplish a discriminating task. In addition, the signal-to-noise ratio and other imaging-specific parameters might vary widely across imaging modalities, making it difficult for predefined features to account for these differences[25].

To find out how the general public feels about artificial intelligence being used in the diagnostic interpretation of screening mammography, Ongena et al. [26] undertook a longitudinal study using an Internet poll for the social science panel on the Dutch population. The 922 female participants ranged in age from 16 to 75. The patient's perspective on the use of artificial intelligence in mammography was studied using five factors: the "Necessity of a human check," "AI as a selector for second reading," "AI as a second reader," "Developer is responsible for error," and "Radiologist is responsible for error[27]." A 5-point Likert scale was created ad-hoc to measure patients' levels of agreement or disagreement in the absence of standardised questionnaires. The authors used the variable "education" to analyse the questions, and they discovered that the perspectives of patients with higher levels of education differed from those with lower levels of education. According to the findings, people who agree that a human review of mammograms is essential are less likely to have favourable opinions of AI due to their education level, and they are more likely to

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prefer personal interaction[28]. Those who perceive human verification as neutral are more likely to view face-to-face discussions of outcomes as unimportant and to view AI as more efficient, maintaining an optimistic perspective of health technology. Patient-perception baselines, patient priorities for AI use cases, and patient-identified evaluation metrics were all determined through a patient engagement workshop that Adams et al[29]. hosted and analysed using qualitative methods. Seventeen patients (eleven females and six males; age and diagnosis were not provided) participated in qualitative interviews. The authors extracted patterns or themes from the textual information. Fear, trust, human connection, and cultural acceptability were the four overarching themes that emerged from early reactions to AI[30]. The public's conception of artificial intelligence was formed by the media and science fiction. Some respondents showed apprehension, while others painted AI as a mysterious and frightening tool. Fear about the unproven AI tool in radiography led to a crisis of confidence. While most participants' lack of understanding translated into scepticism of AI, some showed a readiness to place their faith in AI's results, which could prove more reliable[31]. Some participants were also worried that AI would increase the need for "human empathy" and "the ability to understand with flexibility," suggesting that they felt disconnected from the group as a whole. All participants stressed the need for a straightforward method of explaining the AI findings, as medical terminology often proved too complex or ambiguous. Participants did stress the importance of comprehending their imaging data in order to actively participate in their care and have more fruitful discussions with their providers[32].

Carter et al. [33]: A narrative evaluation of the ethical implications of AI-enhanced doctor-patient communication in radiography was collected by Certainly, patients know very little about health technologies and likely know even less about artificial intelligence systems .

Mendelson [34]: looks at the advantages and disadvantages of using AI for breast imaging. The author emphasised the significance of the potential of AI in radiology in light of the recent decades' progress in the workflow enhancement of AI algorithms and the outcome analyses. In order to aid breast imagers in diagnosis and patient management, AI relies heavily on large amounts of high-quality imaging data. Decisions made by doctors during the survival period were emphasised as being particularly important for their knowledge and expertise[35].

Kapoor et al. [36]: presented a summary of existing resources and solicited ideas for incorporating AI into existing workflows. In this paper, we propose using AI to help radiologists with patient scheduling, worklist management, and the interpretation of diagnostic imaging data. Multiple, intricate operations, from regular screening to report communication, were cited as examples of how AI can be put to use.

The importance of the report communication as the last link in the diagnostic imaging chain was emphasised by Kamalnath et al. [37]. According to the authors, this is a frequently overlooked source of poor care quality. In addition, ML algorithms can be used to accurately identify individualised recommendations for follow-up care based on the detection of specific disease entities in radiology reports. The study's authors stated that feedback report data might be used to facilitate the necessary closed-loop communication for tracking radiologist variation in recommendations for further care [38].

H.A. Haenssle (2022): On average, level-I dermatologists were able to classify lesions with a sensitivity of 86.6% (9.3%) and a specificity of 71.3% (11.2%). The sensitivity increased to 88.9% (9.6%, P = 0.19) while the specificity decreased to 75.7% (11.7%, P 0.05) when more clinical information was available (level-II)[39]. With sensitivities of 86.6% and 88.9%, respectively, the CNN ROC curve demonstrated a greater specificity of 82.5% when compared with level-I (71.3%, P 0.01) and level-II (75.7%, P 0.01) dermatologists. CNN's ROC AUC was higher than dermatologists' mean ROC area (0.86 vs. 0.79, P 0.01). Results obtained by the CNN were very close to those obtained by the top three algorithms in the ISBI 2016 challenge[40].

Boom jho choo (2022): The test dataset consists of 812 photos from 212 patients out of a total of 5017 images from 1269 individuals. For the purpose of prospective validation, we gathered an additional 200 photos from 200 patients[41]. The Inception-Resnet-v2 model achieved an accuracy of 84.6% on the 5-classification task using weighted average accuracy. For stomach cancer and neoplasm, the model's average area under the curve (AUC) was 0.877 and 0.927, respectively. There was a significant performance gap between the Inception-Resnet-v2 model and the top endoscopist in prospective validation (five-category accuracy: 76.4% vs. 87.6%; cancer: 76.0% vs. 97.5%; neoplasm: 73.5% vs. 96.5%; P 0.001)[42]. When it came to distinguishing between stomach cancer and neoplasm, the Inception-Resnet-v2 model and the endoscopist with the lowest performance were statistically indistinguishable (accuracy 76.0% vs. 82.0%).

Areej ulfi (2022): One hundred and forty anonymized mammograms were obtained from Saudi women for screening purposes. Two hundred and eighty-five cases and eight hundred and fifty-five controls were compared for age and body mass index before and after assessing breast density using the Breast Imaging Reporting and Data System (BI-RADS) density categories and a visual analogue scale (VAS)[43]. Volpara DensityTM and predicted VAS (pVAS) were used to quantify density in a sample of 160 cases and 480 controls. Conditional logistic regression was used to assess odds ratios (ORs) between the highest and second categories in BI-RADS and Volpara density grades, and the highest vs lowest quartiles in VAS, pVAS, and Volpara DensityTM. When

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comparing the highest and second highest BI-RADS categories, the OR was 6.69 (95% CI 2.79-16.06), and when comparing the highest and lowest VAS quartiles, the OR was 4.78 (95% CI 3.01-7.58)[44]. In the subset, the odds ratio (OR) for the highest quartile against the lowest quartile was OR = 7.54 (95% CI 3.86-14.74) for VAS, OR = 5.38 (95% CI 2.68-10.77) for pVAS using raw pictures, and OR = 3.55 (95% CI 1.86-6.75) for Volpara Density TM. VAS showed superior discriminating between cases and controls, with a matched concordance score of 0.70 (95% CI 0.65-0.75)[45].

The usefulness of BA techniques may be influenced by a number of factors. One is an individual's socioeconomic position, which includes their living conditions and the quality of their diet, health, and financial and social standing. In order to reach one's full potential, one must have "high" socioeconomic status [46], which is associated with better access to medical care, nutritious food, physical activity, and stable housing. Skeletal maturity may be sped up in those of higher socioeconomic level, according to the literature [47]. Overweight and obesity have been linked to brain development in children, suggesting a connection between poor nutrition and these characteristics [48, 49]. Poor diets, low body weight, and development retardation are more common in people from lower socioeconomic backgrounds [50]. Considering that the TW2 approach was revised in light of concerns about secular change [51], but G&P has never been revised, we questioned the validity of bone age assessment. Our goal was to examine the validity of the G&P and TW3 approaches in the context of the present day United Kingdom.

Khalaf (2023): Using the G&P atlas[52], we found that dividing the cohort into year intervals yielded statistically significant results for different age groups in females and males. Even when just data from Caucasian children was evaluated, these discrepancies (overestimation at age 6 and underestimate at age 12, in females) were remained significant. Despite these sub-group distinctions, no gender-based statistical difference was found between the mean BA and CA. Our results, specifically the mean difference between BA and CA, were compared to those of research that had only examined the Caucasian population in order to provide a more complete picture. According to the G&P norm in males of all ages [53, 54-55], skeletal maturity in Caucasian youngsters occurs at a rate similar to that observed in these investigations. Because the G&P atlas's mean BA is lower than the reference population's in several age groups, other authors caution against using it without caveats [56–57]. Underestimation of boys under the age of 13 and overestimation during adolescence are consistent across various G&P atlas investigations [58–59]. Females may use G&P during puberty, but there was an overestimation of their abilities before the age of 12 [60, 61]. Since BA has progressed so significantly due to secular changes in skeletal maturation, which are thought to be linked to higher standard of living [62, 63, 64, 65], some have argued that a new standard is necessary for exact bone age estimation. Calfee et al. [66] found that G&P underestimated males and girls between the ages of 12 and 15 when their BA was at least 2 years older than their CA. While these other studies relied on the judgement of human raters, our objective software analysis suggests that G&P is still relevant today.

Sasank chalmurty (2023): We compiled a database of 313 318 head CT images and associated clinical reports from roughly 20 different sites in India between 2011 and 2017[67]. This dataset (the Qure25k dataset) was split in half, with half used for algorithm development and the other half for validation. Different data collection centres were employed for the CQ500 validation dataset than those used for the development and Qure25k datasets. We didn't include scans taken after surgery or of patients less than 7 years old. For both the Qure25k and CQ500 datasets, the original clinical radiology report and the consensus of three independent radiologists served as the gold standard[68]. The algorithms were mostly evaluated using areas under the receiver operating characteristic curves (AUCs). The Qure25k dataset included 21 095 scans (mean age = 43 years; 9030 [43%] female patients), while the CQ500 dataset had 214 scans (mean age = 43 years; 94 [44%] female patients) and 277 scans (mean age = 52 years; 84 [30%] female patients) in two separate batches[69]. AUC for detecting intracranial haemorrhage was 0.92 (95% CI 0.91 to 0.93) on the Qure25k dataset (0.90 [0.89 to 0.91] for intraparenchymal, 0.96 [0.94 to 0.97] for intraventricular, 0.92 [0.90-0.93] for subdural, 0.93 [0.91-0.95] for extradural, and 0.90 [0.89 to 0.92] for subarachnoid). The area under the curve (AUC) for cerebral haemorrhage on the CQ500 dataset was 0.94 (0.92–0.97) (0.95 [0.93–0.99], 0.93 [0.87–1.00], 0.95 [0.91–0.99], 0.97 [0.91–1.00], and 0.96 [0.92–0.99]. Calvarial fracture AUCs on the Qure25k dataset were 0.92-0.94, midline shift AUCs were 0.93-0.94, and mass effect AUCs were 0.96-0.87, while corresponding AUCs on the CQ500 dataset were 0.96-0.97, 0.96-0.97, and 0.92-0.92[70].

VI. FUTURE PROSPECTIVE

The psycho-cognitive viewpoints of patients should be taken into account in future studies on AI applications. We propose the abbreviation AIR-IUT to highlight the three essential steps to be considered in the use of AI in the field of radiology and future studies focusing on the patient's experience of the application of AI[71]. Meaning "Inform patients to Understand and Trust the use of AI," the acronym describes a technique in the field of artificial intelligence in radiology. Digital platforms with illustrated movies to enlighten patients should be implemented in the future, delivering trustworthy educational tools that might be supplied in the waiting rooms. By actively involving and informing patients during the screening process, digital engagement

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has the potential to boost compliance, lessen patients' fear of the unknown about health technology and psychological symptoms, and improve patients' decision-making during treatment[72]. At the same time, it may be possible to create a training programme to improve doctor-patient communication during the diagnostic process. As a result of taking such a course, clinicians will be better able to communicate with their patients using patient-friendly terminology (i.e., jargon words will be clarified or replaced with simpler phrases) and an empathetic approach, paying special attention to each individual's emotional health[73].

VII. CONCLUSION

In conclusion, when artificial intelligence (AI) is utilised in diagnosis, clinicians should hone their communication skills and patients should be involved primarily through being informed on the functioning of medical instruments used to make their diagnosis. The lack of patient understanding of AI and its impact on trust and communication between doctors is a recurrent theme throughout the studies we gathered. Patients should be educated and involved in every step of their clinical journey, therefore it's important for them to understand the diagnostic tools their doctors employ and how they function. We believe that telling patients about the advancements made by the exceptional AI in our industry will assist to increase their level of trust in it.

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